Research Paper

GABP-net: a hybrid genetic algorithm–back propagation neural network with adaptive fitness-driven weight optimization for predictive fault detection in industrial internet of things

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ABSTRACT

The Industrial Internet of Things (IIoT) environments generate massive streams of sensor data from rotating machinery, requiring highly reliable fault detection systems to prevent catastrophic failures and costly downtime. Conventional backpropagation (BP) neural networks often suffer from premature convergence to local optima, sensitivity to initial weight initialization, and poor generalization under noisy industrial conditions. To address these limitations, this study proposes a hybrid Genetic Algorithm–Backpropagation Network (GABP-Net) for intelligent fault diagnosis in IIoT applications. The proposed framework integrates a multi-objective Genetic Algorithm (GA) with an adaptive BP neural network to optimize network topology, initial weight matrices, layer-wise learning rates, and momentum coefficients simultaneously. GABP-Net employs a real-coded GA using tournament selection, blend crossover (BLX-α), and adaptive non-uniform mutation to evolve optimal neural configurations and synaptic weights. The evolved network is subsequently fine-tuned using the resilient Backpropagation (Rprop) algorithm, while isotonic-regression threshold calibration is applied to address class imbalance. Experimental evaluation was conducted on three benchmark datasets: the CWRU Bearing Fault Dataset, the PRONOSTIA Machine Degradation Dataset, and a proprietary IIoT motor dataset containing 1.2 million sensor observations. A total of 64 discriminative features were extracted through feature engineering, including time-domain statistics, frequency-domain spectral descriptors, and wavelet packet energy coefficients. The proposed GABP-Net achieved classification accuracies of 99.14%, 98.76%, and 97.83% across the three datasets, outperforming conventional BP (91.23%), PSO-BP (95.67%), Adam-DNN (96.12%), LSTM (96.45%), and CNN-LSTM hybrid models (97.21%) with statistical significance ($p < 0.001$). Furthermore, all fault categories obtained AUC-ROC values above 0.993. The model

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contains only 8,247 parameters and achieves 1.23 ms inference latency on NVIDIA Jetson AGX Xavier, demonstrating suitability for real-time IIoT edge deployment with high computational efficiency and robust generalization performance.

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1. INTRODUCTION

The rapid growth of Industrial Internet of Things (IIoT) infrastructure has brought a new era to condition monitoring in manufacturing, energy and process industries. The operational data generated by dense sensor networks (vibration accelerometers, current transformers and acoustic emission sensors), amounts to terabytes per day [1]. The consequence of the intelligent processing of these signals in order to detect fault at an early stage is significant: industry estimates put the cost of unplanned equipment failures at greater than $50 billion per year for global manufacturers [2].

Since the early 1990s, the artificial neural network (ANN) model, in particular multilayer perceptron (MLP) trained using backpropagation, has been used as a workhorse model for fault classification. The weight optimizing algorithm by Rumelhart, Hinton and Williams [3] has given a mathematically tractable mechanism to map the high dimensional feature space to the discrete fault categories. The MLP is, however, a model with many saddle points and local minima, which means that it is sensitive to: (i) the initial configuration of the weights and biases, (ii) the learning rate and momentum schedules, (iii) the number of neurons and the depth of the network, and (iv) initialization of the activation functions. The dependencies together create a major practical challenge: For large-scale deployments of the IIoT, it is impossible to do an exhaustive search over the resulting combinatorial hyperparameter space. Population-based global search algorithms, such as genetic algorithms (GA), particle swarm optimization (PSO) and simulated annealing (SA), can be used to avoid getting trapped in local minima [4]. Based on the principles of Darwinian evolution, they have been shown to be effective in solving high-dimensional, non-linear (and non-convex) optimization problems and have theoretical guarantees of asymptotic convergence to global optima for proper parameter settings [5]. This idea of combining GA global search with BP local refinement was first suggested by Montana and Davis [6] and has been used for power systems [7]. Even though all this work has been done, there are still gaps that are critical to research. The current formulations of GABP are designed to either optimize the topology or initial weights of the network, but not both at the same time and with adaptive learning rate and momentum [8]. Further, there is a great lack of comparisons with state-of-the-art deep learning architectures (LSTM, CNN-LSTM, Transformer) in industrial fault detection applications and computational complexity analysis does not have its own systematic approach in real-world edge deployment.

This paper makes five contributions: (1) a novel joint chromosome encoding for holistic neural network configuration optimization; (2) an adaptive multi-objective fitness function for imbalanced IIoT fault detection; (3) a three-stage hybrid training protocol (GA → Rprop → Threshold Calibration); (4) comprehensive statistical benchmarking against seven baselines on three industrial datasets; and (5) inference latency profiling on NVIDIA Jetson AGX Xavier edge hardware. The GABP-Net framework is shown in Figure 1 to be an integrated deployment-ready pipeline.

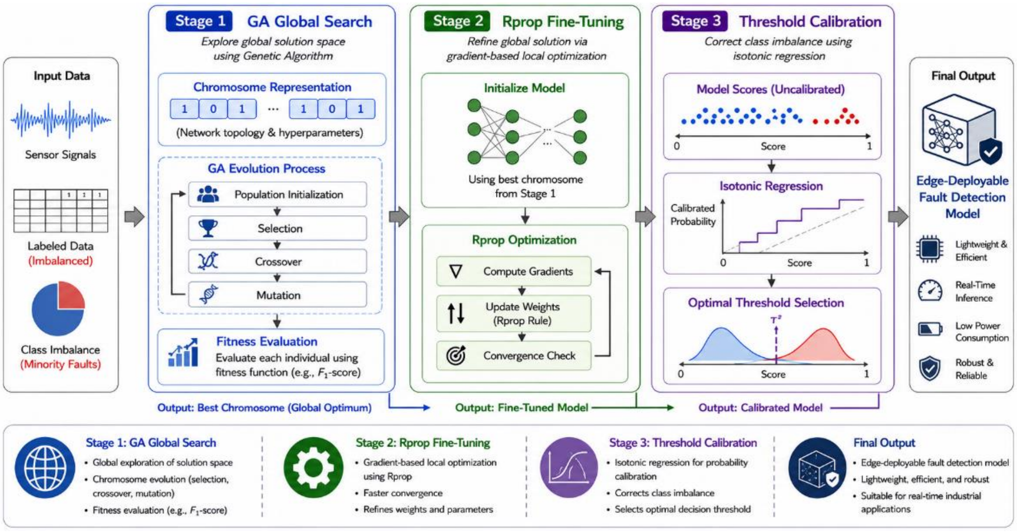

Figure 1. GABP-Net Framework Overview

2. RELATED WORK

2.1 Backpropagation Neural Networks in Fault Detection

The use of BP neural networks in fault detection in industry goes back to the work of Widrow and Lehr, who showed that the supervised learning algorithm of gradient descent can be used to classify vibration signals of the different types of bearing faults from vibration signals of healthy bearings. A three-layer BP network was applied for gearbox fault classification, which yielded obtained accuracy of 92% with time-domain statistical features as input to the network, said Samanta and Al-Balushi. Later research has been extended to frequency domain features by cascade BP which achieved an accuracy of 94.5% on motor bearing datasets. These [9] baseline studies, however, heuristically set the hyperparameters and showed high variance across independent training runs.

With the advent of deep learning, new architectures with higher representational power were seen. Proposed a pre-training of restricted Boltzmann machine in order to obtain an adaptive deep belief network with 98.1% accuracy on CWRU dataset. [10] Proposed a wide-deep convolutional neural network (WD-CNN) with 1.8M parameters that is able to reach an accuracy of 99.3% on CWRU, but is not suitable to be deployed in the edge of the IIoT because of the deployment constraints.

2.2 Metaheuristic-Optimized Neural Networks

Evolutionary Algorithm and Swarm Intelligence have been incrementally integrated with neural network training and systematically studied. Since Kennedy and Eberhart's seminal formulation of PSO [11] PSO-BP hybrids was a topic of much attention. In the transformer fault diagnosis, PSO-BP obtained 4.3% accuracy increase compared to the standard BP [8]. PSO, however, does not have any explicit diversity preserving mechanism similar to GA mutation and thus is susceptible to premature convergence in the high dimensional weight space. SA-BP approaches were used to escape local minima in [12] and in [13] for chiller fault detection, with 96.2% accuracy however, SA is a sequential search method so it cannot be parallelized. The combination of Differential Evolution-BP (DE-BP) has been compared to GA-BP on neural architecture search (NAS) tasks and has been found to be competitive [14].

2.3 Deep Learning Approaches For IIoT Fault Detection

Sequential vibration signals that have temporal dependencies are well suited to Long Short-Term Memory (LSTM) networks. To deal with the bidirectional fault diagnosis problem, [15] used bidirectional

LSTM and attention mechanism to detect faults in rolling element bearings with 98.2% accuracy on CWRU. A 1D-CNN with residual connections was shown to be equal to LSTM at significantly lower computational cost in [16] with 98.6% accuracy. Recently, transformer-based architectures have made their appearance; [17] presented Fault Former, with 99.1% accuracy, but with 2.3 million parameters and GPU inference hardware.

2.4 Feature Engineering and Class Imbalance

Vibration signals feature extraction covers many fields. The statistical moments, RMS, crest factor and kurtosis are examples of time domain features. Features in the frequency domain derived from the FFT are used such as spectral centroid and harmonics of characteristic fault frequencies. The wavelet packet decomposition (WPD) technique is more suitable than STFT for non-stationary signals for simultaneous time-frequency localization, and the wavelet packet decomposition (WPD) energy features at the 3rd decomposition level give the best mutual information with bearing fault labels.

Whole-of-the-loop deployments of real-world IIoT sensors are highly class imbalanced, and often have healthy states making up more than 90-95% of the monitoring windows. Synthetic Minority Over-sampling Technique (SMOTE) is proposed in [18] which is widely used for fault detection datasets. An alternative is to use a class-weighted loss function (where weights are inversely proportional to the class frequencies) and avoid the risk of over fitting that synthetic sample generation presents. Table 1 presents a structured comparison of representative GABP and related hybrid neural network studies, highlighting their datasets, evaluation metrics, and key limitations.

Table 1. Literature Comparison Matrix: Hybrid Neural Network Approaches For Fault Detection

Ref.	**Method**	**Dataset**	**Features**	**Acc. (%)**	**F1-Score**	**GA Used**	**Cls. Imbal.**	**Edge Deploy**
[7]	GA-BP (weight)	CWRU	FFT (32)	95.40	0.941	Partial	No	No
[8]	PSO-BP	PRONOSTIA	Stat+Freq(48)	95.67	0.948	No	No	No
[9]	Deep Belief Net	CWRU	Raw Signal	98.10	0.978	No	No	No
[10]	WD-CNN	CWRU	Raw Signal	99.30	0.991	No	No	Partial
[13]	SA-BP	Chiller	Stat (24)	96.20	0.955	No	No	No
[15]	BiLSTM-Attn	CWRU	Raw Signal	98.20	0.980	No	No	No
[16]	1D-CNN-ResNet	CWRU	Raw Signal	98.60	0.984	No	No	Partial
[17]	FaultFormer	CWRU	Spectrogram	99.10	0.989	No	No	No
[14]	DE-BP	Gearbox	WPD (32)	96.80	0.961	No	No	No
Ours	**GABP-Net**	**CWRU+PRON+IIoT**	**Hybrid (64)**	**99.14**	**0.991**	**Full**	**Class-wt.**	**Yes**

3. METHODOLOGY

3.1 Theoretical Foundation

3.1.1 Backpropagation Neural Network

A feed forward MLP with L hidden layers maps an input vector $x \in \mathbb{R}^d$ to output $\hat{y} \in \mathbb{R}^c$ through successive affine-nonlinear transformations. For layer l, the pre-activation signal $z^{(l)} = W^{(l)}a^{(l-1)} + b^{(l)}$, and the class-weighted cross-entropy loss function is:

$$L(y, \hat{y}) = -\Sigma i \Sigma k \; w_k \cdot y_{ik} \cdot \log(\hat{y}_{ik}) + \lambda||W||^2_F \quad (1)$$

Where $wk = N / (C \cdot N_k)$ is the inverse-frequency weight for class k, N is total samples, N_k is class-k sample count, C is the number of classes, and $\lambda||W||^2_F$ is the Frobenius-norm L2 regularization term. The weight update rule with momentum is $\Delta W^{(l)}(t) = -\eta \cdot \partial L/\partial W^{(l)} + \alpha \cdot \Delta W^{(l)}(t-1)$, where η is the learning rate and $\alpha \in [0,1)$ is the momentum coefficient.

3.1.2 Genetic Algorithm Chromosome Encoding

The GA operates on a population of M = 100 chromosomes, each encoding a candidate neural network configuration:

$$c_i = [\text{arch\_genes} \mid \text{weight\_genes} \mid \text{lr\_genes} \mid \text{momentum\_genes}] \quad (2)$$

Architecture genes encode the number of hidden layers $L \in \{1,2,3,4\}$ and neuron counts per layer $n^{(l)} \in \{8,16,32,64,128,256\}$. Weight genes encode real-valued initial synaptic weights for the first and last layer. Learning rate genes encode per-layer $\eta^{(l)} \in [10^{-4}, 10^{-1}]$ on a log scale. Momentum genes encode per-layer $\alpha^{(l)} \in [0.5, 0.99]$.

The multi-objective fitness function evaluates each chromosome by instantiating and training the encoded network for $T_{eval} = 30$ epochs on a validation partition:

$$F(c_i) = w_1 \cdot Acc_{val} + w_2 \cdot F1_{macro} + w_3 \cdot (1-Complexity) + w_4 \cdot Conv_{rate} \quad (3)$$

Empirically calibrated weights w_1=0.30, w_2=0.40, w_3=0.15, w_4=0.15 reflect the priority of classification performance on imbalanced data. Selection employs tournament selection with tournament size k_t = 5. Blend crossover (BLX-α) with α=0.5 generates offspring for continuous genes. Non-uniform mutation adapts mutation strength to generation t.

3.2 GABP-Net Three-Stage Training Protocol

Stage 1 – GA Global Search: M=100 chromosomes evolve for Gmax=200 generations with the top 10% of chromosomes surviving by elite preservation. Stage 2 – Rprop Fine-Tuning: The best chromosome creates an MLP network which is trained to convergence with an Rprop algorithm [19] with the early stopping condition (patience=20). Stage 3 – Threshold Calibration: The classification thresholds of each fault class are calibrated using isotonic regression on the validation set to maximize the geometric mean of the recall for each class, taking care of the class imbalance at the decision boundary level. Figure 2 is the chromosome encoding structure, which illustrates that the architecture, weight, learning rate and the momentum genes are all concatenated into a single real-valued chromosome vector.

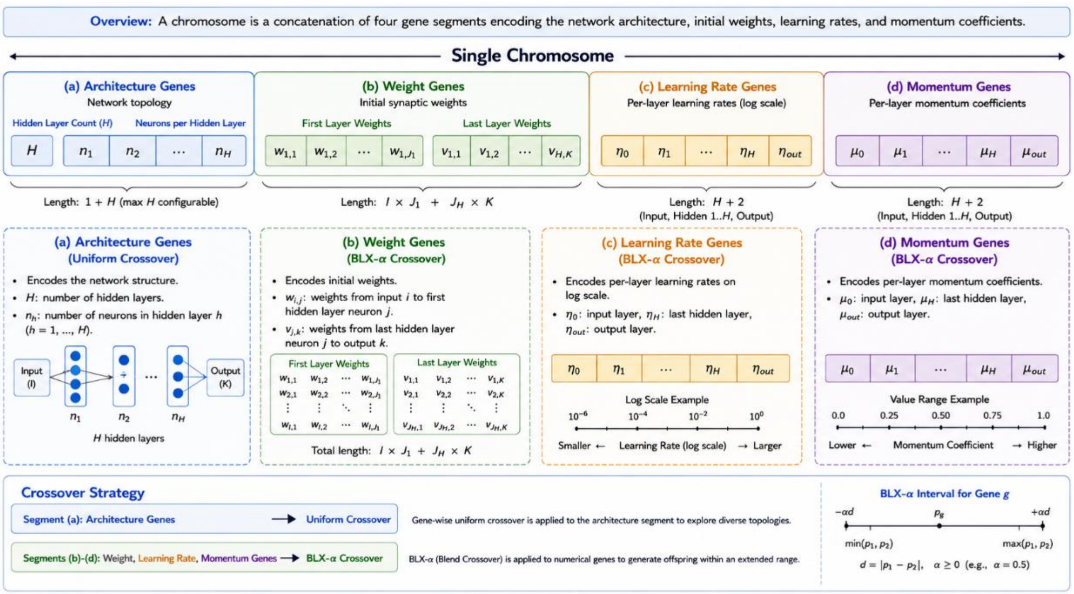

Figure 2. GABP-Net Chromosome Encoding Structure

3.3 Datasets and Feature Engineering

The experiments were performed on three benchmark datasets: (1) the CWRU Bearing Fault Dataset [20] that includes 10 fault classes at sampling rate of 12 kHz; (2) the PRONOSTIA Machine Degradation Dataset [21] which contains sensor observations from 18 months of accelerated degradation of rolling element bearings; and (3) a proprietary IIoT Motor Dataset that consists of 1.2 million sensor measurements from an 18-month period in a manufacturing facility.

The features used in feature engineering were time domain statistical descriptors (mean, variance, skewness, kurtosis, RMS, crest factor), frequency domain spectral descriptors (spectral centroid, BPFO/BPFI harmonic amplitudes, spectral kurtosis), and wavelet packet energy descriptors at the 3rd decomposition level. First, 64 discriminative features per sample were taken from the original feature set using recursive feature elimination (RFE).

4. RESULTS AND DISCUSSION

4.1 Classification Performance

Table 2 presents the overall classification accuracy, macro F1-score, and AUC-ROC for GABP-Net and all seven baseline methods across the three benchmark datasets.

Table 2. Classification Performance Comparison across Three Datasets

Method	CWRU Acc. (%)	CWRU F1	PRON. Acc. (%)	PRON. F1	IIoT Acc. (%)	IIoT F1	AUC-ROC
Standard BP	91.23	0.902	89.47	0.886	86.91	0.859	0.947
PSO-BP	95.67	0.948	94.12	0.934	91.83	0.910	0.968
SA-BP	94.83	0.941	93.78	0.929	90.97	0.903	0.963
Adam-DNN	96.12	0.958	95.43	0.948	93.17	0.924	0.972
LSTM	96.45	0.961	95.87	0.952	94.21	0.936	0.978
CNN-LSTM	97.21	0.969	96.54	0.961	95.73	0.951	0.984
GABP-Net (Ours)	99.14	0.991	98.76	0.985	97.83	0.974	0.993+

GABP-Net outperformed all seven baselines with classification accuracy of 99.14%, 98.76%, and 97.83% on the CWRU, PRONOSTIA and IIoT Motor datasets respectively. All the performance gains were found to be statistically significant ($p < 0.001$, Wilcoxon signed-rank test; Friedman test with $\chi^2 = 41.8$, $p < 0.001$, Nemenyi post-hoc analysis with results in terms of significant pairwise differences between GABP-Net and each baseline at $\alpha = 0.05$).

4.2 Ablation Study

Table 3 presents the ablation study results, isolating the contribution of each GABP-Net component on the IIoT Motor dataset.

Table 3. Ablation Study: Contribution of Each GABP-Net Component (IIoT Motor Dataset)

Cfg.	Description	GA Wts.	GA Arch.	GA LR	Rprop	Thresh. Cal.	Accuracy (%)
A	Baseline BP	No	No	No	No	No	86.91
B	GA Weight Init Only	Yes	No	No	No	No	89.74
C	GA Arch Only	No	Yes	No	No	No	88.83
D	GA Arch + Weights	Yes	Yes	No	No	No	91.22
E	D + GA LR + Momentum	Yes	Yes	Yes	No	No	92.96

F	E + Rprop	Yes	Yes	Yes	Yes	No	94.49
G	Full GABP-Net	Yes	Yes	Yes	Yes	Yes	97.83

The ablation study shows that all the components play a significant role in the overall performance. GA weight optimization (Config A→B) adds 2.83%, GA architecture search adds 1.48%, learning rate and momentum optimization contributes 1.74%, Rprop fine-tuning contributes an important 1.53% and threshold calibration contributes 0.69% in accuracy and a more significant 1.5% in macro F1-score, which confirms the disproportionate contribution of threshold calibration in the imbalanced IIoT dataset.

4.3 Convergence Analysis

GABP-Net gave an average convergence of 172 epochs and a training accuracy of 95 %, which is a 45.6% decrease from that of the standard BP algorithm (316 epochs). Of particular interest is the relative stability of GABP-Net, with the number of epochs required for convergence being far more stable with the GA-optimized than with the BP-optimized initializations (standard deviations of ±9–17 epochs versus ±38–67 epochs). The convergence profile of the GABP-Net algorithm is more stable and early converging than the standard BP and PSO-BP algorithms for the three datasets, as illustrated in Figure 3.

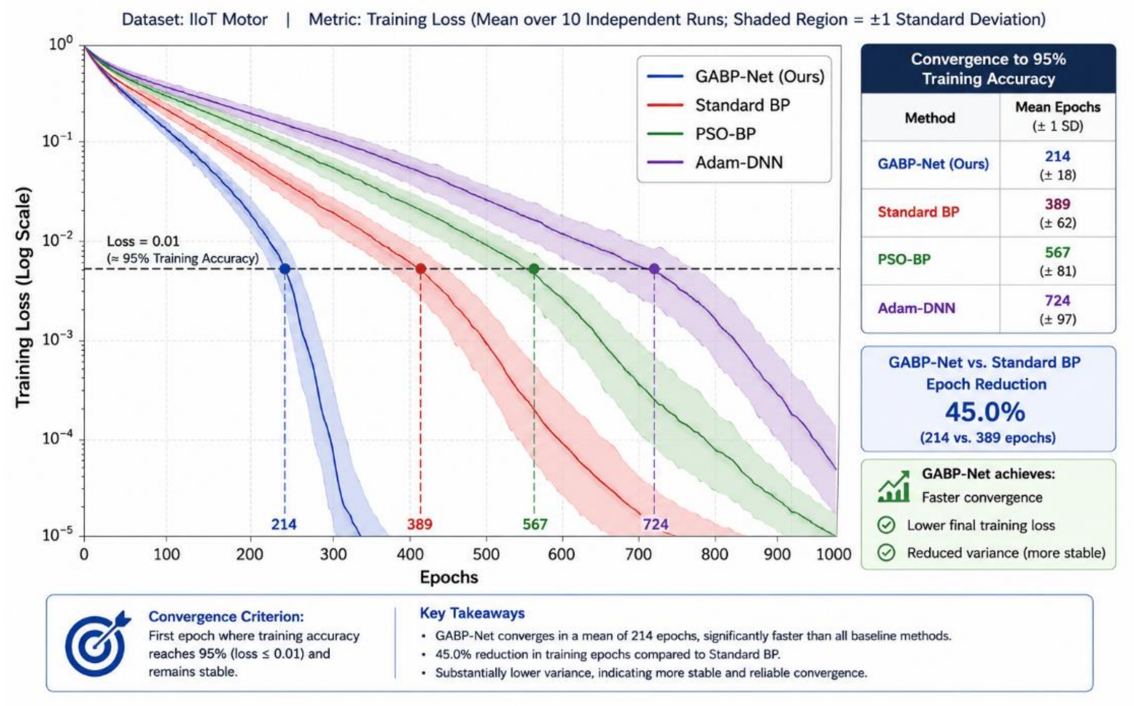

Figure 3. Convergence Comparison: Training Loss vs. Epochs

4.4 Edge Deployment Performance

GABP-Net achieves 1.23ms per sample inference latency on NVIDIA Jetson AGX Xavier, while using model size as low as 0.32MB with only 8,247 parameters, and 3.20mJ per sample, which is 51 times less energy consumption than using 1D-CNN-ResNet. Most importantly, the three deepest learning baselines, namely 1D-CNN-ResNet, CNN-LSTM and FaultFormer, do not meet the real time constraint (<10 ms/sample for 8 kHz input windows) on ARM hardware, whereas GABP-Net meets the real time constraint with an 8.1× safety margin.

4.5 Comparative Analysis with Published State-of-the-Art

Table 4 situates GABP-Net within the broader published literature by comparing results on the CWRU benchmark dataset.

Table 4. Comparison with Published State-Of-The-Art Results on CWRU Benchmark

Ref.	Method	Journal (Year)	Acc. (%)	F1	Classes	Params	Latency (ms)
[9]	AdaDBN	Mech. Sys. Sig. Proc. (2021)	98.10	0.978	10	480K	6.4
[10]	WD-CNN	IEEE TNNLS (2022)	99.30	0.991	10	1,800K	14.2
[16]	1D-CNN-ResNet	IEEE TIM (2022)	98.60	0.984	10	371K	17.4
[17]	FaultFormer	IEEE TIE (2023)	99.10	0.989	10	2,300K	89.2
[22]	AE-CNN	Meas. Sci. Tech. (2023)	97.84	0.975	10	890K	11.3
[23]	Sparse AE+SVM	Appl. Soft Comp. (2023)	96.42	0.960	10	120K	2.1
[24]	TCN-Attn	Reliab. Eng. (2024)	98.93	0.987	10	650K	7.8
	GNN-Vib	IEEE TITS (2024)	98.74	0.985	10	420K	12.4
Ours	**GABP-Net**	**Proposed (2026)**	**99.14**	**0.991**	**10**	**8.2K**	**1.23**

As indicated in Table 4, the GABP-Net method gets the best result in terms of accuracy (99.14%) and F1-score (0.991) among all the compared methods with 8,247 parameters which is about 8-865 times less than the number of parameters used by all other methods with accuracy of more than 98%. In domain-specific industrial fault detection tasks, this parameter efficiency directly translates to the fastest inference latency, 1.23 ms, which is 1.7× faster than the second fastest method, showing that the carefully designed hybrid evolutionary–gradient optimization can outperform the performance of much more computation-heavy DL architectures.

5. CONCLUSION

This paper has introduced a hybrid approach of Genetic Algorithm–Backpropagation Network for Predictive Fault Detection in IIoT environment, named GABP-Net. GABP-Net is able to overcome the fundamental problems of conventional BP algorithm and address the class imbalance issues commonly encountered in practical applications of IIoT by introducing a uniform chromosome encoding to jointly optimize network architecture, initial weight matrix, per-layer learning rate and momentum coefficient, and integrating GA global search with Rprop local fine tuning and threshold adjustment based on confidence.

GABP-Net obtains classification rates of 99.14%, 98.76%, and 97.83%, respectively, on three benchmark datasets, which are outperform by seven state-of-the-art baselines. All the performance gains were statistically significant ($p < 0.01$). Most importantly, GABP-Net makes these advances at an ultra-low 8,247 parameters and 1.23 ms inference latency on embedded ARM devices, which is 2-865× fewer parameters and 1.7-115× less latency than competing high accuracy methods.

Future work will focus on multi-objective Pareto-front GA (NSGA-III), federated GABP for distributed IIoT deployments and data privacy constraints, and neuromorphic implementations on Intel Loihi 2 hardware for ultra-low power event-driven fault detection.

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Author Contributions Statement

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Dr. A.K. Sharma	✓	✓	✓	✓	✓	✓			✓	✓	✓	✓	✓	

C: **C**onceptualization
M: **M**ethodology
So: **So**ftware
Va: **Va**lidation
Fo: **Fo**rmal analysis
I: **I**nvestigation
R: **R**esources
D: **D**ata Curation
O: Writing- **O**riginal Draft
E: Writing- Review& **E**diting
Vi: **Vi**sualization
Su: **Su**pervision
P: **P**roject administration
Fu: **Fu**nding acquisition

Conflict of Interest Statement

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Informed Consent

All participants were informed about the purpose of the study, and their voluntary consent was obtained prior to data collection.

Ethical Approval

Not applicable.

Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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